Effects of Mandated Driver Pay Increases On the Gig Economy: Evidence from New York City

Dmitri Koustas,¹ James Parrott² and Michael Reich³

Abstract

The advent of app-dispatched services such as Uber and Lyft have dramatically changed urban transportation. Increased ridership on these services has raised concerns about low pay and working conditions of drivers, as well as increased congestion costs in metropolitan areas. In this paper, we analyze a series of major regulatory changes enacted in 2018 and 2019 in New York City. These include a minimum driver pay standard intended to increase the hourly wage to over $17 and a $2.75 per trip congestion surcharge. We make use of a very large, confidential administrative dataset at the driver-trip level containing half a billion app rides starting or ending in New York City from August 2017 to the present. Our data and setting allow us to examine activity across all the app-dispatch companies, including among multi-app drivers, in contrast to much of the existing literature that uses only administrative Uber data. Our research design uses event study methods and exploits how the policies bind differently across app companies, across times of the day and days of the week, across geographic areas, and depending on company pay and pricing policies and supply and demand patterns in the period before implementation.

We find that the pay standard increased average driver pay per trip by somewhat more than the pay standard itself predicts. Approximately 85% of the pay increase is passed on in the form of higher fares, although smaller platforms also responded by reducing effective commission rates. For a 1% increase in pay per trip due to the pay standard, we estimate total trips on a given route have fallen by around -0.7%, which is consistent with overall demand being responsive but inelastic, and overall driver pay including tips increased by around 0.8%. We also examine data on individual drivers before and after implementation of these policies, finding the pay standard persistently increased hourly wages and hours for the next 11 months for which we have data. Turning to the congestion charge, a 1% increase the congestion charge reduced trips per hour on a route by 0.7%. We also estimate the congestion charge increased average speed on a route, with an elasticity of 0.17%. Our findings provide insight on key structural parameters specific to the industry, such as labor supply and demand elasticities, and paint a somewhat different picture than currently found in the literature. They should help better inform regulation of app-based dispatch services as well as the broader “gig economy.”

¹ University of Chicago
² The New School
³ University of California, Berkeley
The following figure illustrates one of our main sources of variation, the differential binding of the pay standard across hours of day and days of the week.

(a) Share of Trips Counterfactual Pay Standard Expected to Bind

(b) Counterfactual Dollar Increase Per Trip Due to Pay Standard

(c) Counterfactual Percentage Increase Per Trip Due to Pay Standard

Notes: Using the formula for the pay standard, we calculate counterfactual driver pay based on trips data from February-June 2018 before the pay standard would have gone into effect. Panel (a) shows the share of trips for which a counterfactual pay standard would have binded. Panel (b) shows the counterfactual dollar increase in pay due to the pay standard. Panel (c) is the counterfactual percentage increase in driver pay.
The following figures show event-studies exploiting route-level variation in the binding of the pay standard. We find that routes with more exposure to the pay standard see a substantial relative increase in average pay and fares.

Fig 2. Event Study Results: Driver Pay Per Trip
(a) Driver Pay Per Trip: Lowest versus Highest Quartiles of Exposure
(b) Difference

Fig 3. Event Study Results: Base Passenger Fares Per Trip
(a) Base Passenger Fares Per Trip: Lowest versus Highest Quartiles of Exposure
(b) Difference

Notes: The left-hand panel plots the $\beta$ event study coefficients from the following specification:

$$y_{pd,t,h}^q = \alpha_{pd,dow(t),h}^q + y_{w(t)}^q + \sum_{w} \beta_{w}^q 1\{w = w(t)\} + \epsilon_{pd,t,h}^q$$

where $q$ denotes quartile of counterfactual exposure to the pay standard, $pd$ denotes a pickup-dropoff borough pair, $t$ indexes date, and $h$ indexes hour of day. $w(t)$ is a function mapping date
to week. We plot the results for quartiles 1 (lowest) and quartiles 4 (highest) exposure. The right-hand panel plots the $b$ event study coefficients from the following specification:

$$y_{pd,t,h} = a_{pd,dow(t),h} + c_{w(t)} + \sum_w b_w 1(w = w(t)) \times 1(q(dow(t), i) = 4) + e_{pd,t,h}$$

Where $1(q(dow(t), i) = 4)$ is an indicator for quartile 4. We restrict the sample to quartiles 1 and 4 so the interpretation is the difference between quartiles 1 and 4 shown in the left-hand panel. In both specifications, we omit weeks in June 2018, so event study coefficients are relative to this month. The first set of figures use as an outcome average driver pay per trip. The second set use average fare per trip. These outcomes are available from August 2017-June 2018, and again from February 2019. Standard errors clustered at the week level. The dotted vertical line in the figure indicates the week the pay standard went into effect.
Fig 4. Driver-Level Regressions

The following figures show results for hours and the hourly wage estimated at the driver level. Hourly pay initially increases by around 3% for every 1% increase in expected pay per trip, stabilizing to around 2%. Hours increase by around 1%.

(b) Elasticity of Hours to the Counterfactual Increase in Pay From Pay Standard

(a) Elasticity of the Hourly Wage to the Counterfactual Increase in Pay From Pay Standard

Notes: Figure plots β coefficients from the following specification estimated at the driver-week level:

\[ y_{i,t} = \sum_{m \in M} \beta_m 1(m(t) = m) \times z_i + \alpha_i + \alpha_t + \epsilon_{i,t} \]

We aggregate data to the week level. \( i \) indexes driver and \( t \) indexes week. We consider two outcomes: hourly pay and hours. Hours are determined based on time at least one app is on. This outcome is available over the whole period. Results for hours are shown in the left-hand panel. We omit January 2019, the month before the pay standard went into effect, so event study coefficients are relative to this month. Hourly pay is calculated as total weekly pay divided by total weekly hours. This outcome is shown in the right-hand panel. Pay outcomes are only available from August 2017-June 2018, and again from February 2019. We omit the event-study coefficient for June 2018, so results are relative to this month. Standard errors clustered at the individual driver level. The dotted vertical line in the figure indicates the week the pay standard went into effect.